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Fast Calorimeter Simulation in LHCb

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In HEP experiments CPU resources required by MC simulations are constantly growing and become a very large fraction of the total computing power (greater than 75%). At the same time the pace of performance improvements from technology is slowing down, so the only solution is a more efficient use of resources. Efforts are ongoing in the LHC experiments to provide multiple options for simulating events in a faster way when higher statistics is needed. A key of the success for this strategy is the possibility of enabling fast simulation options in a common framework with minimal action by the final user. In this talk we will describe the solution adopted in Gauss, the LHCb simulation software framework, to selectively exclude particles from being simulated by the Geant4 toolkit and to insert the corresponding hits generated in a faster way. The approach, integrated within the Geant4 toolkit, has been applied to the LHCb calorimeter but it could also be used for other subdetectors. The hits generation can be carried out by any external tool, e.g. by a static library of showers or more complex machine-learning techniques. In LHCb generative models, which are nowadays widely used for computer vision and image processing are being investigated in order to accelerate the generation of showers in the calorimeter. These models are based on maximizing the likelihood between reference samples and those produced by a generator. The two main approaches are Generative Adversarial Networks (GAN), that takes into account an explicit description of the reference, and Variational Autoencoders (VAE), that uses latent variables to describe them. We will present how both approaches can be applied to the LHCb calorimeter simulation, their advantages as well as their drawbacks.

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1. Introduction

During Run 2 the simulation of physics events at LHCb has taken about 80% of the distributed computing resources available to the experiment [1]. The increase in number of events that will need to be simulated in Run 3 to match the higher luminosity and trigger rate will place an extreme burden on the computing resources. To face this situation it is necesary to develop new ways to significantly increase the speed of the simulation.

In a typical minimum bias event about 55% of the CPU time used by Geant4 to simu late particle transportation is spent in the calorimeter system. Given these number, in the effort of developing a faster detector simulation it is natural to start from the calorimeter.

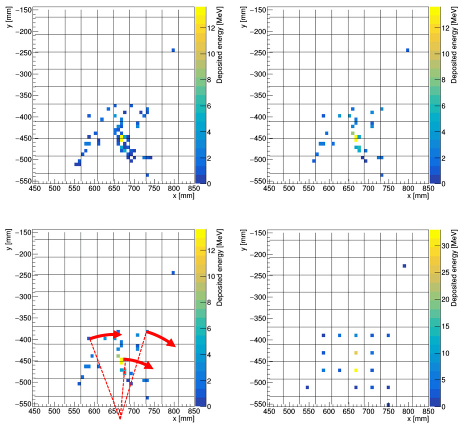
A number of fast simulation options are available or under development in LHCb to complement the standard simulation based on Geant4 [2]. In this short paper we consider two of them: using pre-simulated library of calorimeter responses, and generative model trained on the pre-simulated sample to speed up simulation of response in the electromagnetic calorimeter (ECAL).

The LHCb detector [3] is equipped with ECAL that employs a "shashlik" technology of alternating 4 mm thick scintillators tiles and 2 mm thick lead plates arranged perpendicular to the beam pipe. The detector is not longitudinally segmented but adopt a variable lateral segmentation, because the hit density varies by two orders of magnitude over the calorimeter surface. A segmentation into three different sections has been chosen for the ECAL, with square cell sizes of approximately 40, 60 and 120 mm in the inner, middle and outer regions, respectively.

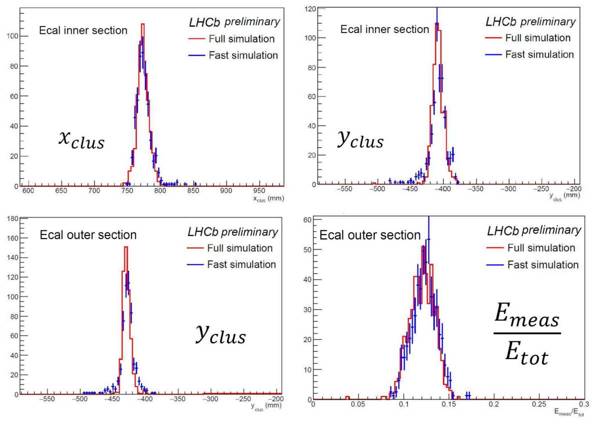
2. Library Approach

Detailes for this approach may be found elswhere [4]. To reduce the number of parameters in produced response library, the cell transverse area is divided into small subregions, or "points" and a library of points is built from simulated incident particles with fixed values for particle position and azimutal angle. Hence, for a given particle species only the binnings in energy and incidenÑĄe angle remain. An example of point distribution in the ECAL produced by an incident photon with energy O(1) GeV is shown in Fig. 1a, top-left plot, where each square of the grid represents the transverse area of an ECAL cell and the colour scale indicates the deposited energy in MeV. Then two or more points belonging to the same cell area and with associated energy below a given threshold may be merged locally to simplify the collection, i.e. to reduce the number of points stored in the library. This is exemplified in top-right plot. In the next step the points are shifted and rotated according to the position of incidence and azimuthal angle of the particle with respect to the values for which the library was built. This is a key aspect of the point library. The collection of points represents a good model of the shower projection in the transverse plane, so that its shift and rotation gives a good description of the shower produced by a translated and rotated incident particle. The rotation of the points around the position of incidence of the particle is exemplified in thebottom-left plot. Finally, the calorimeter hits are created by summing the energies of those transformed points which fall into the same cell area. This is shown in the bottom-right plot, where the colour in the central region of the cell indicates the total deposited energy, in MeV.

The accuracy of the calorimeter simulation based on point libraries has been tested through the comparison with detailed simulation using photons generated at the calorimeter entrance with



(a) Schematic illustration of the point library operating principle. More details are given in section 2.



(b) Comparison of photons simulated with Geant4 ("Full simulation") and with the point libraries ("Fast simulation")

Figure 1: Library approach.

various energies and angles of incidence. The coordinates of the hit cluster centre are defined as weighted with energies mean coordinate of cluster cells. The top plots compare the cluster position distributions in the case where the entrance point of the fully simulated photons coincide with the one used to build the library, thus only rotation is necessary for the procedure described above. The bottom plots compare distributions for cluster position and measured energy in the case where the fully simulated photons are generated in the outer sector. In this case the points had to be rotated and then translated but the agreement does not worsen, proving that the idea behind the point library works.

3. Generative Model Approach

The idea of this approach is to treat simulations as a black-box and replace the traditional Monte Carlo simulation with a method based on Generative Adversarial Networks [5]. Wasserstein GAN [6] with gradient penalty are considered to be state-of-the-art technique for image producing, so a tool based on this particular approach is used. Architecture of the used Neural Network and details on training the generative model are present elsewhere [7].

After the generative model is built and trained, we start with comparing original clusters, produced by full Geant4 simulation and clusters generated by the trained model for the same parameters of the incident particles: the same energy, the same direction, and the same position on the calorimeter face. Corresponding images for four arbitrary parameter sets are presented in Fig. 2. These images demonstrate very good visual similarity between simulated and generated clusters.

Then we continue with quantitative evaluation of the proposed simulation method. While generic evaluation methods for generative models exist, here we base our evaluation on physics-driven similarity metrics. For this presentation we selected few cluster properties which essentially drive cluster properties used in the reconstruction of calorimeter objects and following physics analysis. If initial particle direction is not perpendicular to the calorimeter face, produced cluster is

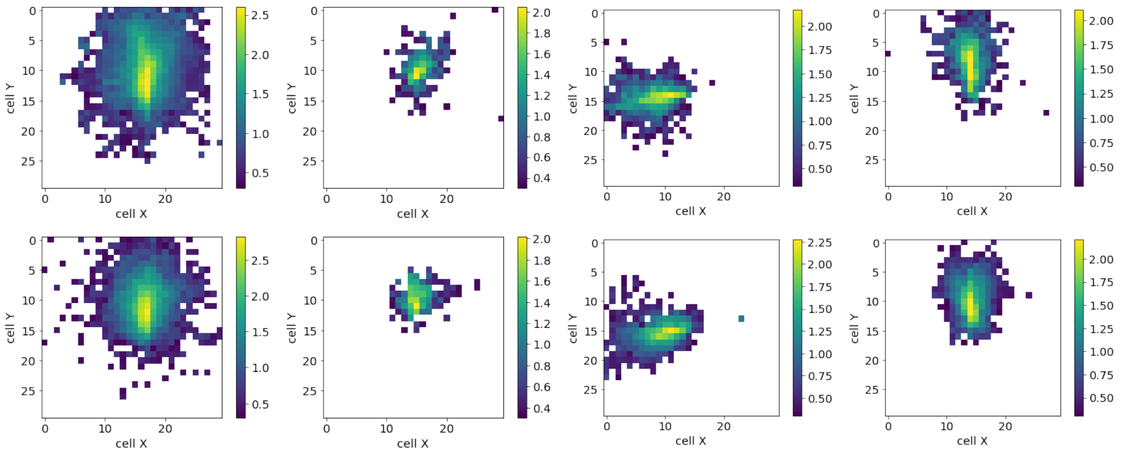


Figure 2: Showers generated with GEANT4 (first row) and the showers, simulated with our model (second row) for three different sets of input parameters. Color represents $log_{10}(\frac{E}{MeV})$ for every cell.

elongated in that direction. Therefore we consider separately cluster width in the direction of the initial particle and in the transverse direction. Spatial resolution, that is the distance between center mass of the cluster and the initial track projection to the shower max depth, is another important characteristics affecting physics properties of the cluster. Cluster sparsity, that is the fraction of cells with energies above some threshold, reflects marginal low energy properties of the generated clusters. These characteristics are presented in Fig. 3.

4. Conclusions

In LHCb there is an ongoing effort to develop fast simulation alternatives to the nominal detector simulation to face the current and future limitations of CPU resources with respect to the size of the necessary simulated samples. In the detailed simulation based on Geant4 more than 50% of the CPU time is spent in the calorimeter system. We use different approaches to develop faster simulation of the calorimeter. Both library and generative model approaches are encouraging in terms of time gain and simulation accuracy. The use of a point library as opposed to a more standard cell hit library allows to significantly improve the output accuracy for the same size of the library. We also prove that Generative Adversarial Networks are a good candidate for fast simulating of high granularity detectors typically studied for the next generation accelerators. We have successfully generated images of shower energy deposition with a condition on the particle parameters such as the momentum and the coordinate using modern generative deep neural network techniques.

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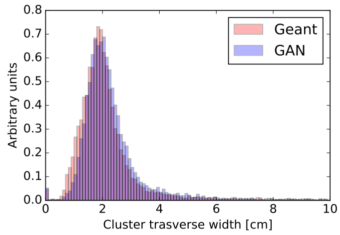
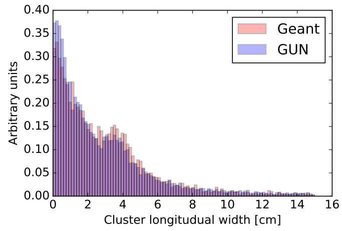
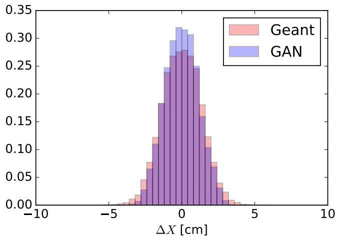


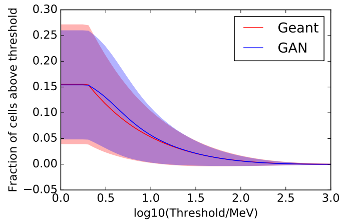
(a) The transverse width of real and generated clusters



(b) The longitudinal width of real and generated clusters



(c) ΔX between cluster center of mass and the true particle coordinate



(d) The sparsity of real and generated clusters

Figure 3: Generated images quality evaluation including described physical characteristics.

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